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Artificial Neural Networks Model for Photosynthetic Rate Prediction of Leaf Vegetable Crops under Normal and Nutrient-Stressed in Greenhouse

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ABSTRACT

Photosynthesis is one of the essential processes in plant physiology that produces glucose and oxygen to support plant growth. Nutrient stress conditions will affect the photosynthetic rate in plants. The model predicting photosynthetic rates based on environmental conditions, nutrients, and plant types will be highly beneficial for farmers in tweaking these variables to maximize plant photosynthesis. This research focused on assessing the impact of nutrient stress on the photosynthetic rate in leaf vegetable crops and aimed to create a model using artificial neural networks (ANN) to predict photosynthetic rates under nutrient-stress conditions. Leaf vegetable crops were cultivated in a greenhouse using the NFT hydroponic system with eight nutrient conditions. This paper introduces an ANN model featuring nine input variables, ten hidden layers, and a single output. This model aims to elucidate the relationship between these inputs and the output parameter. The statistical analysis revealed a notable disparity in the CO_2 assimilation rate among leaf vegetable crops subjected to nutrient stress treatment. The constructed ANN model demonstrated strong performance, achieving an R^2 value of 0.9416, an RMSE of 1.5898 during training, and an R^2 value of 0.9271 with an RMSE of 1.9649 in validation. A combination of statistical analysis and ANN modeling accurately explained the relationship and influence of input parameters, especially nutrient stress conditions, on the photosynthetic rate of leaf vegetable plants cultivated hydroponically in a greenhouse.

1. Introduction

Greenhouses meet the need for sustainable agricultural production regardless of the season (Maraveas *et al.* 2023). In addition, greenhouses are also expected to protect plants from pests and diseases to increase the productivity of crop yields. Greenhouse technology can enhance both the quality and quantity of crop yields, decrease the likelihood of production failures due to climate fluctuations, and reduce the time to harvest for vegetable production compared to traditional open-field systems. So, it is expected that the leaf vegetable cultivation process can be carried out sustainably with greenhouse technology because it is possible to change and control the microclimatic conditions around the plants (Trujillo 2018). In general, the cultivation of leaf vegetables in greenhouses is carried out using a hydroponic system. The hydroponic system is one of the effective technologies in plant cultivation that can increase growth and productivity compared to conventional cultivation (Pomoni *et al.* 2023).

Environmental conditions of plant growth play an important role in cultivation management as an effort to increase productivity. All factors influencing plant growth, such as sunlight, CO_2 levels, temperature,

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air humidity, water, and nutrients, must be controlled using a mix of technologies to ensure they are consistently available to the plants for producing high-quality and high-quantity plant products (Ampim *et al.* 2022). These environmental factors influence gene expression, protein levels, chlorophyll content, photosynthesis, and metabolite production in leaf vegetables (Du *et al.* 2020). As part of an important environmental factor, plants need sufficient nutrients to grow and perform their physiological functions properly (Aleksandrov 2022; Veazie *et al.* 2022).

Photosynthesis is one of the essential processes in plant physiology that produces glucose and oxygen to support plant growth (Kayoumu *et al.* 2023). Nutrient stress conditions in plants will affect the rate of photosynthesis in plants. Nitrogen (N) and phosphorus (P) are the nutrients that most significantly impact photosynthesis, as they are essential substrates in photosynthetic reactions (Hu *et al.* 2021). Lack of N nutrients in plants can reduce the rate of photosynthesis because it inhibits the formation of chlorophyll, which results in premature aging of plants and reduces plant productivity (Mu and Chen 2020). Meanwhile, P nutrient deficiency in many experiments caused a reduction of photosynthetic rate by decreasing the opening of stomata in the leaves so that less CO_2 is captured (Meng *et al.* 2021; Kayoumu *et al.* 2023; Shu *et al.* 2023). In addition, the lack of other macronutrients (K, Ca, and Mg) and micronutrients will also affect the rate of photosynthesis in plants (Sitko *et al.* 2019; de Souza Osorio *et al.* 2020).

The photosynthetic rate can be assessed by measuring the CO_2 assimilation rate within plant leaves (Erniati *et al.* 2024). Moreover, the photosynthetic rate is impacted by several critical factors, including sunlight intensity, air temperature, relative humidity, water and nutrient availability, atmospheric CO_2 concentration, and chlorophyll content within the leaves (Lenni *et al.* 2020). Plants' environmental parameters, nutrients, and photosynthetic processes have a complex relationship. Yet, the impact of nutrients on photosynthetic rates warrants further exploration. Thus, there is a need to develop a novel model capable of elucidating the connection between these parameters and the photosynthetic rate in leaf vegetable plants.

According to Nelissen and Gonzales (2020), computational modeling for plant growth and development is becoming an exciting interdisciplinary research field. The models are designed with agricultural applications in focus, considering diverse physiological processes and ecological interactions. Artificial neural networks (ANNs) are robust models that explain the correlation between input and output parameters (Suhardiyanto 2023). ANN is extensively employed as an intelligent technique in intricate multidimensional modeling (Pu *et al.* 2022). Basir *et al.* (2021) stated that ANN models could predict crop yields more accurately than regression models and proved to be a superior method for accurately estimating crop yields. Since the condition of the greenhouse is non-linear and can change every time, some studies choose to use ANN models to simulate, predict, optimize, and control every process that occurs in the greenhouse (Escamilla-Garcia *et al.* 2020).

The use of ANN in building a plant photosynthesis simulation model in the greenhouse can increase the accuracy of the photosynthetic rate model in plants (Pu *et al.* 2022). The model for predicting photosynthetic rates based on environmental factors, nutrients, and plant characteristics will significantly aid farmers in fine-tuning these variables to optimize photosynthetic rates in plants (Erniati *et al.* 2024). Photosynthetic rate models in vegetable crops have been applied to lettuce (Jung *et al.* 2016; Lenni *et al.* 2020), Chinese mustard (Gao *et al.* 2021), spinach (Kaneko *et al.* 2022), and cucumber (Zhang *et al.* 2020; Wei *et al.* 2023). However, further investigation into the photosynthetic rate model affected by plant nutrient stress is necessary. Hence, this research aimed to evaluate the effect of nutrient stress on plant photosynthetic rates and constructed a model for photosynthetic rates in leaf vegetable plants under normal and nutrient-stressed conditions using artificial neural networks (ANN).

2. Materials and Methods

2.1. Experimental Condition

The study was carried out between February and March 2024 at the Siswadhi Soepardjo Leuwikopo Field Laboratory, Department of Mechanical Engineering and Biosystems, IPB University, utilizing a 6 × 12 meter piggyback type greenhouse equipped with a nutrient film technique (NFT) hydroponic system (Figure 1). Equipment for measurement instruments in data collection consisted of a portable photosynthetic instrument (LI-COR) type LI-6800, digital web camera (Xiaovv XVV-6320S), Davis Vantage Pro 2 weather station, photo box set, measuring cup, EC/TDS and pH meter (EZ9908), and light meter (UT383 Digital Luxmeter). The materials used in this study consisted of pak choi and romaine lettuce vegetable seeds, AB mix nutrients, Rockwool, and a set of NFT hydroponic installations.

The leaf vegetable crops cultivated were pak choi mustard (*Brassica rapa* var. chinensis) and romaine lettuce (*Lactuca sativa* var. romana), with 78 plants for each species and treatment. The leaf vegetable crops were planted in the NFT hydroponic system with a spacing of 18.5 × 15 cm. The solution used was AB mix nutrient formulated based on Hoagland's standard solution modified by Veazie *et al.* (2022) into eight treatments with different nutrient compositions (Table 1). Over time, the nutrient solution concentration was periodically adjusted to suit the plants' growth stages while ensuring the pH level of the solution was maintained at 5.5 to 7.0.

2.2. Dataset Collection

Data collection on the environment, nutrient solution, and plants for photosynthetic rate measurement was conducted on March 20, 2024, when the plants were 24 days after transplanting (DAT). The environmental parameters monitored included solar radiation, air temperature, and relative humidity within the greenhouse. Environmental data measurements were conducted using a Davis Vantage Pro 2 weather station for one day at five-minute intervals. Meanwhile, the nutrient solution parameters measured were the total dissolved solids (TDS) value and pH of the solution using a TDS meter and pH meter. Furthermore, the measured plant parameters were the vegetation index value in green-red vegetation index (GRVI) and plant photosynthetic rate expressed in CO_2 assimilation rate. GRVI is a plant vegetation index based on RGB values of leaf vegetable images. GRVI values were calculated using Equation 1. CO_2 assimilation rate was assessed using a portable photosynthetic instrument (LI-COR) type LI-6800 on 26 leaf vegetable crop samples from all treatments, and

Table 1. Treatment of nutrient concentration

Treatment	Macronutrient composition (mg L^{-1})					
	N	P	K	Ca	S	Mg
Control	150.0	20.0	296.0	75.0	40.0	25.0
-N	0.0	20.0	296.0	75.0	40.0	25.0
-P	150.0	0.0	296.0	75.0	40.0	25.0
-K	150.0	20.0	0.0	75.0	40.0	25.0
0% of control	0.0	0.0	0.0	0.0	0.0	0.0
50% of control	75.0	10.0	148.0	37.5	20.0	12.5
150% of control	225.0	30.0	444.0	112.5	60.0	37.5
200% of control	300.0	40.0	592.0	150.0	80.0	50.0
	Macronutrient composition (mg L^{-1})					
	Fe	Mn	Cu	Zn	B	Mo
All treatment	4.02	0.99	0.48	0.49	0.30	0.07

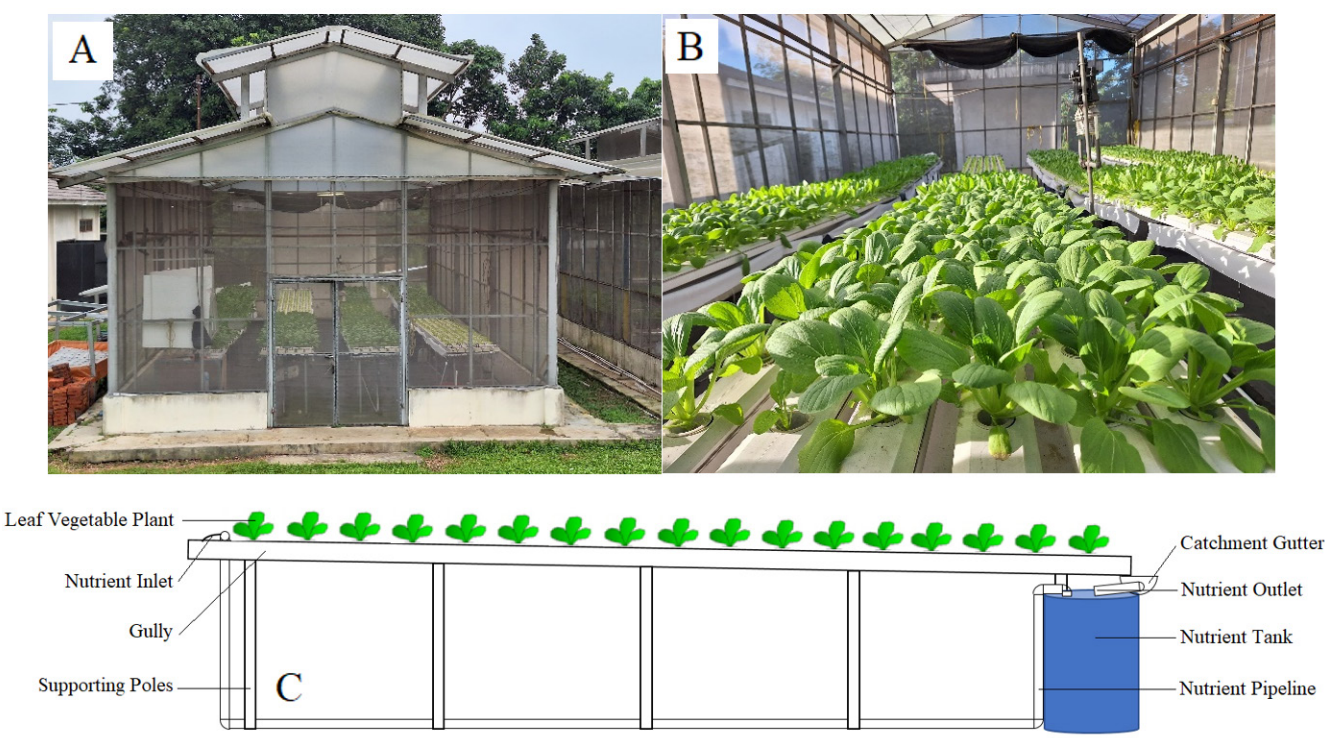

Figure 1. (A) Greenhouse, (B) NFT hydroponic system for leaf vegetable cultivation, and (C) schematic diagram of NFT hydroponic system works

a total of 208 CO_2 assimilation rate measurement data were obtained. CO_2 assimilation rate measurements were conducted under natural light conditions with a range of Photosynthetic Photon Flux Density (PPFD) values at 208.6 to 265.2 µmol m^{-2} s^{-1}. The selected leaf sample was one of the largest leaves on the vegetable crops. Figure 2 shows measuring the CO_2 assimilation rate in leaf vegetable crops. CO_2 assimilation rate data were then statistically analyzed by the Analysis of Variance (ANOVA) test and Duncan's Multiple Range Test (DMRT) using IBM SPSS Statistics 23.0 application to see the effect of nutrient stress treatment on the photosynthetic rate of leaf vegetable crops.

$$\mathrm{GRVI} = \frac{G - R}{G + R} \quad (1)$$

Where,
G : green value
R : red value

2.3. ANN-based Photosynthetic Rate Model Development

An artificial neural networks (ANN) model was developed to predict the CO_2 assimilation rate in leaf vegetable crops. The model was created using the Python programming language and comprised three layers (input, hidden, and output layers) with the backpropagation learning method. The architecture included nine parameters in the input layer (air temperature, air relative humidity, solar radiation, nutrient solution TDS, nutrient solution pH, concentrations of N, P, and K in the nutrient solution, and GRVI), ten nodes in the hidden layer, and one parameter in the output layer (CO_2 assimilation rate), as shown in Figure 3. The parameters in the input layer are the main parameters that affect the photosynthetic rate in leaf vegetable crops based on environmental, nutrient, and plant factors. Furthermore, the hidden layer between the input layer and output layer functions to help the model understand complex and non-linear patterns in the data by processing each input value into an activation function before finally being forwarded to the output layer. The activation function chosen for both the hidden and output layers was the logistic (sigmoid) function (Equation 2).

$$f\,(\mathrm{net}) = \frac{1}{1 + e^{-\mathrm{net}}}\text{, where} \quad (2)$$

$$\mathrm{net} = \Sigma_{i=0}^{n}\, x_i\, w_i \quad (3)$$

Where,
x_i : input value,
w_i : input weight,
n : number of inputs

A total of 208 datasets from each parameter were utilized to construct a CO_2 assimilation rate prediction

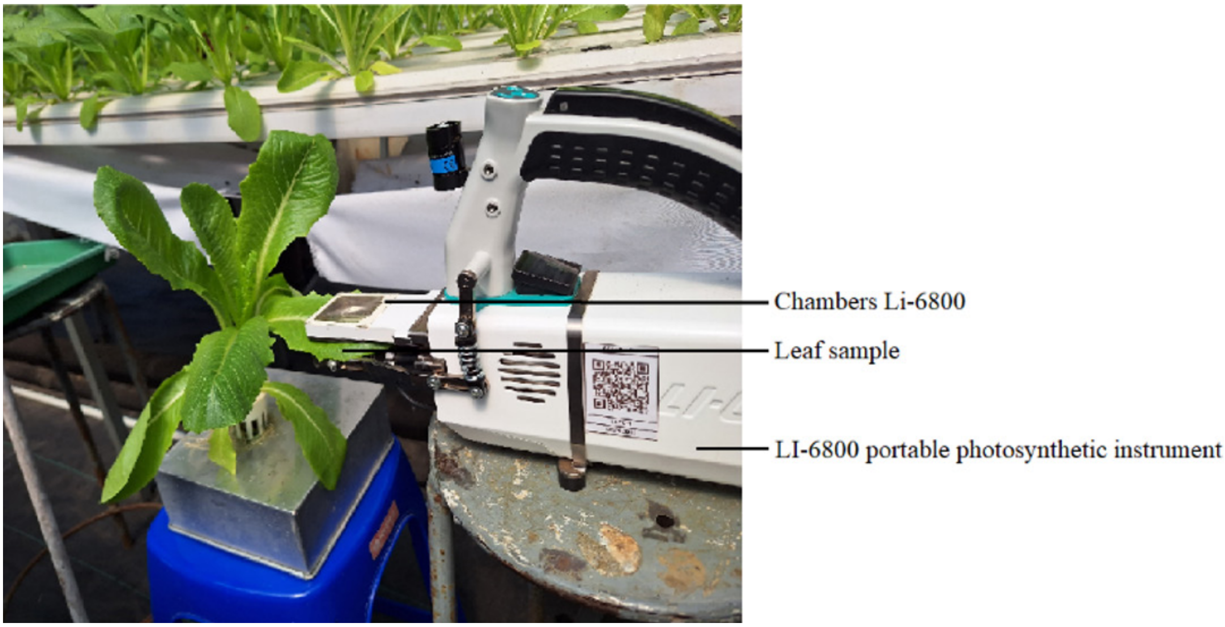

Figure 2. Measurement process of CO_2 assimilation rate in leaf vegetable crops using LI-6800 portable photosynthetic instrument (LI-COR)

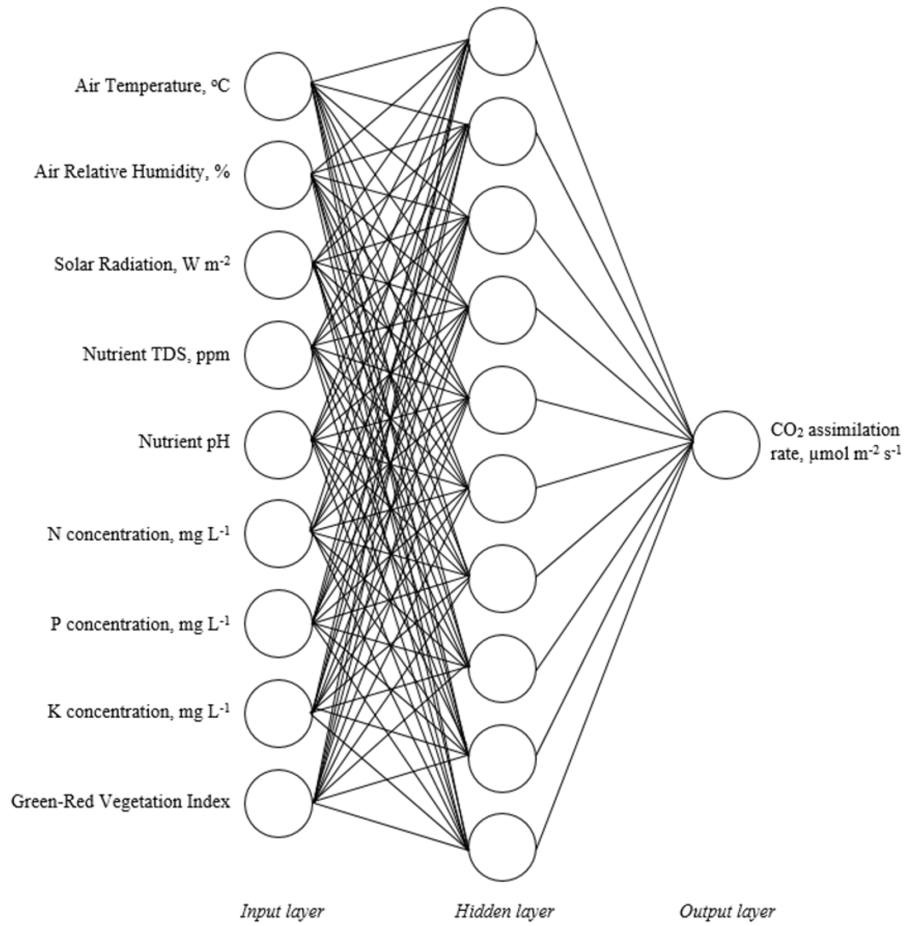

Figure 3. Artificial neural networks (ANN) model architecture

model using ANN. The dataset was split, with 67% allocated for training and 33% for validation (Suhardiyanto 2023). During the training phase, weight values determine the relationships between the input and output parameters (Lenni *et al.* 2020). Additionally, the developed ANN model was subjected to validation against actual measurement data. The performance of the ANN model was then evaluated based on the coefficient of determination (R^2) and Root Mean Square Error (RMSE), as outlined in equations 4 and 5.

$$R^2 = 1 - \left[\frac{\Sigma_{i=0}^{n}(Y_p - Y_a)^2}{\Sigma_{i-0}^{n}(Y_p - \bar{Y}_a)^2}\right] \quad (4)$$

$$RMSE = \sqrt{\frac{\Sigma\,(Y_p - Y_a)^2}{n}} \quad (5)$$

Where,

Y_p : predicted value of the ANN model
Y_a : actual measurement value
$\bar{Y}_a$: average of the actual measurement values
n : number of datasets

3. Results

3.1. Microclimate in Greenhouse

The microclimate conditions within the greenhouse, including solar radiation, air temperature, and relative humidity, were captured in measurement data taken on March 20, 2024, when the plants were 24 days after transplanting (DAT), as shown in Figure 4. The measurements were conducted in one day because the microclimate data used as input parameters for ANN to predict photosynthetic rate were also data taken on the same day as the measurement of plant photosynthetic rate. The maximum solar radiation entering the greenhouse reached 288 W m^{-2} at noon. The maximum air temperature in the greenhouse reached 36.3°C at 14:00, and the minimum air temperature was 20.7°C at 07:00. Meanwhile, the maximum air humidity reached 95%, and the minimum was 55%.

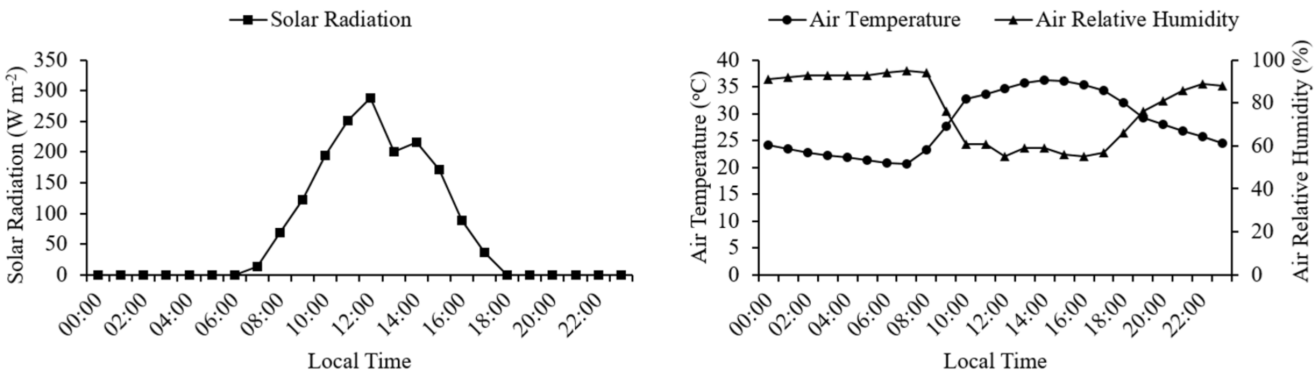

Figure 4. Microclimate conditions in the greenhouse

3.2. Nutrient Condition and Vegetation Index of Leaf Vegetable Crops

In addition to microclimate parameters in the greenhouse, nutrient solution conditions and plant vegetation index were also measured to be used as input parameters in developing the ANN model of CO_2 assimilation rate. The condition of total dissolved solids (TDS) and pH of the nutrient solution in each treatment when the crops were 24 DAT can be seen in Figure 5. The provision of different nutrient compositions in each treatment showed different TDS values for the nutrient solution. Additionally, the pH of the nutrient solution remained within the range of 5.5 to 7.0 across all treatments.

The plant vegetation index used as an input parameter for the ANN model is the Green-Red Vegetation Index (GRVI). It can be seen that nutrient deficiency treatment affects the GRVI value of leaf vegetable crops cultivated hydroponically in the greenhouse. The highest GRVI value was obtained in pak choi plants with a value of 0.24 in the control, 50%, 150%, and 200% treatments. Meanwhile, the lowest GRVI value was obtained in romaine lettuce plants with a value of 0.07 in the -N and 0% treatments (Figure 6).

3.3. Photosynthetic Rate of Leaf Vegetable Crops

Measurement data of CO_2 assimilation rate underwent statistical analysis using the IBM SPSS Statistics 23.0 application to assess the impact of nutrient stress treatment on the photosynthetic rate of leaf vegetable crops. Table 2 displays the outcomes of Photosynthetic Photon Flux Density (PPFD) values and the statistical analysis regarding the CO_2 assimilation rate in pak choi and romaine lettuce. Statistical analysis was conducted using the One-Way ANOVA method by comparing the average value of the CO_2 assimilation rate from each treatment to see if there was a significant difference. Further investigation into differences in CO_2 assimilation rate resulting from nutrient stress treatment was conducted using Duncan's Multiple Range Test (DMRT) at the 5% significance level. The statistical evaluation results show how much difference the effect of nutrient stress treatment has on the CO_2 assimilation rate of leaf vegetable plants.

3.4. ANN Model Performance for Predicting Photosynthetic Rate

Artificial neural network (ANN) models can explain complex patterns of relationships between input and output parameters in predicting photosynthetic rates in plants. The effectiveness of the ANN model in forecasting the photosynthetic rate of hydroponically grown leaf vegetables can be evaluated by examining the R^2 and RMSE values acquired during both the model's training and validation process. Regression analysis comparing the predicted CO_2 assimilation rate by the ANN model with the actual measurements resulted in a linear equation during the training process, with a slope of 0.9394, intercept of 0.6915, R^2 of 0.9416, and RMSE of 1.5898. Meanwhile, the ANN model validation process produced a linear equation with a slope of 0.9766, intercept of 0.0994, R^2 of 0.9271, and RMSE of 1.9649, respectively (Figure 7).

4. Discussion

Photosynthetic activity in plants is influenced by environmental factors (Glanz-Idan and Wolf 2020). The microclimate within the greenhouse, comprising solar radiation, air temperature, and relative humidity, are ecological factors influencing the photosynthetic rate of hydroponically grown leaf vegetable crops. Solar radiation serves as the primary energy source for

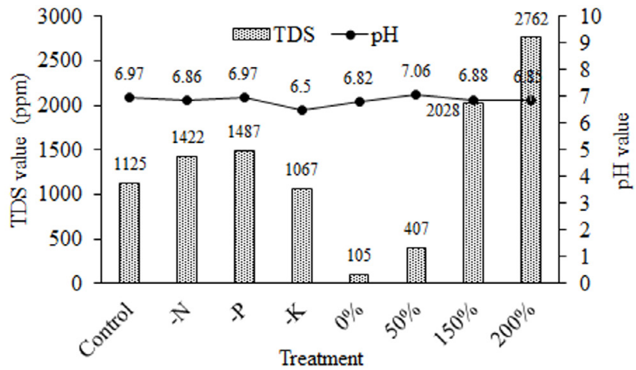

Figure 5. Total dissolved solids (TDS) and pH condition of nutrient solution in each treatment on March 20, 2024

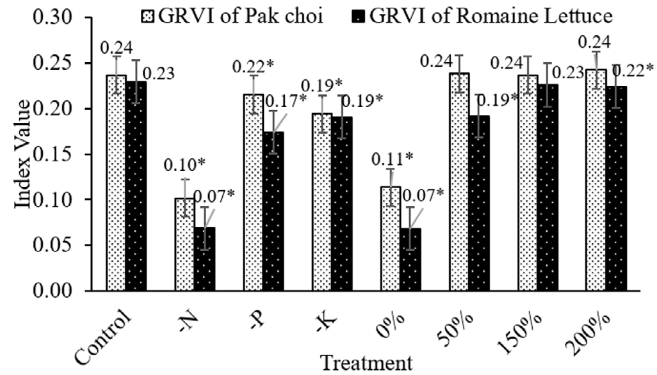

Figure 6. Green-Red Vegetation Index (GRVI) values of pak choi and romaine lettuce in each treatment (note: * indicate the treatment is significantly different to control)

Table 2. PPFD and CO_2 assimilation rate of pak choi and romaine lettuce calculated as mean values and standard deviation (SD), minimum values (Min) and maximum values (Max) with a certain replication (*n*)

Vegetable crop	Treatment	*n*	PPFD (µmol m^{-2} s^{-1})				CO_2 assimilation rate (µmol m^{-2} s^{-1})			
			Mean	SD	Min	Max	Mean	SD	Min	Max
Pak choi	Control	12	227.9	6.9	218.6	232.7	11.82^{b}	2.40	8.55	13.95
	-N	16	258.4	1.2	257.6	260.4	3.08^{a}	0.65	2.65	4.17
	-P	12	263.5	0.9	262.2	264.2	11.87^{b}	2.74	8.21	14.36
	-K	11	249.2	6.9	243.7	257.9	13.94^{c}	1.95	10.88	15.26
	0%	16	233.5	2.7	229.9	236.2	3.82^{a}	0.55	3.01	4.49
	50%	11	212.0	3.1	208.6	216.1	15.08^{cd}	0.08	14.91	15.19
	150%	12	218.5	4.9	214.3	225.1	15.67^{d}	0.34	15.19	16.09
	200%	9	260.2	1.6	258.1	261.6	17.15^{e}	0.17	16.90	17.30
Romaine lettuce	Control	11	250.6	3.0	246.6	253.8	11.51^{E}	0.19	11.24	11.74
	-N	16	248.5	9.6	236.6	260.7	2.01^{A}	0.11	1.85	2.18
	-P	13	258.9	0.6	258.1	259.3	7.83^{C}	0.61	7.16	8.68
	-K	15	222.8	2.9	218.9	225.4	6.64^{B}	1.23	5.04	7.97
	0%	20	224.5	6.5	217.9	232.8	1.82^{A}	0.26	1.43	2.17
	50%	11	209.6	0.8	209.0	210.9	11.98^{E}	0.80	10.92	12.73
	150%	11	238.1	7.8	230.1	247.3	10.45^{D}	1.41	8.71	12.08
	200%	12	264.0	1.4	262.1	265.2	13.11^{F}	0.60	12.36	13.82

The same letter indicates the treatment is not significantly different at the 5% DMRT test

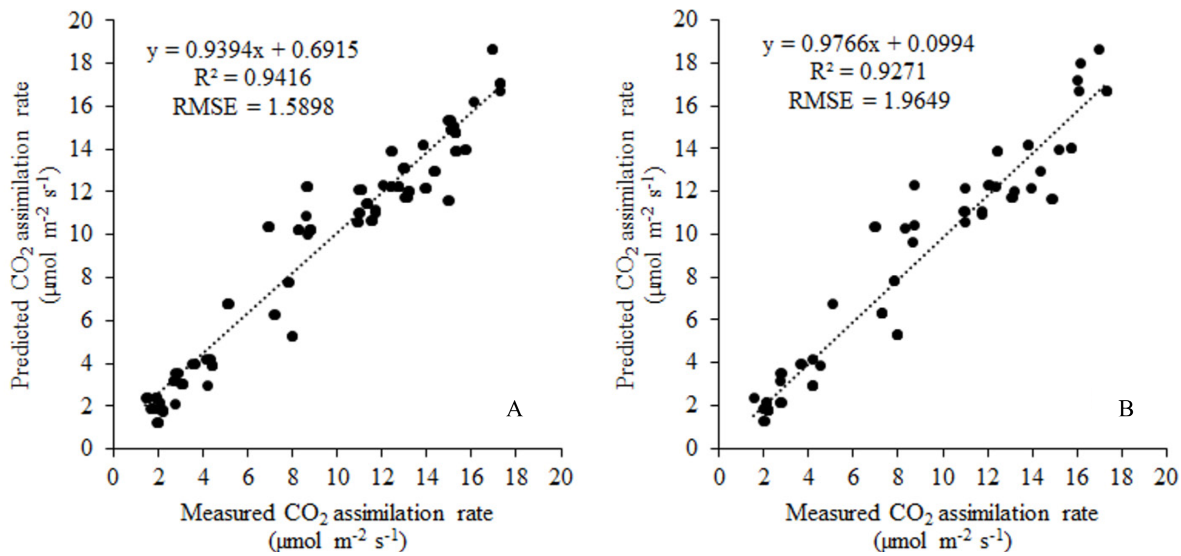

Figure 7. Results of training (A) and validation (B) for the ANN model in predicting the CO_2 assimilation rate of leaf vegetable crops

the photosynthesis process in plants (Yang *et al.* 2021). Meanwhile, the air temperature and relative humidity affect the activity of enzymes that accelerate the reaction of the photosynthetic process in plants (Wei *et al.* 2023). The vegetation index can also be an indicator to predict the photosynthesis process in plants (Liu *et al.* 2022). GRVI is one of the vegetation indices sensitive to leaf color changes in plant canopies due to nutrient stress conditions. The GRVI value indicates plant phenology due to its sensitivity to color variations within the plant canopy (Motohka *et al.* 2010).

Symptoms of nutrient stress in plants are usually characterized by changes in color, shape, and size of leaves that can be seen visually (Kamelia *et al.* 2020; Lu *et al.* 2023). Changes in leaf color due to nutrient stress in leaf vegetables can be shown by the difference in GRVI values of pak choi and romaine lettuce plants (Figure 6). The GRVI values in -N, -P, -K, and 0% treatment significantly differed from the Control treatment in pak choi and romaine lettuce. N, P, and K nutrient deficiency conditions reduce the GRVI value in leaf vegetables. The decrease in GRVI value due to nutrient deficiencies affects the photosynthetic rate in leaf vegetable crops. This correlation shows that the GRVI value is one of the vegetation index parameters that can describe the photosynthetic rate of plants due to nutrient stress conditions in leaf vegetable crops.

Nutrient stress conditions also impact the photosynthetic rate of plants (Ikkonen *et al.* 2021). Based on the statistical analysis results in Table 2, nutrient stress treatment substantially influences the CO_2 assimilation rate in leaf vegetable crops. A nitrogen deficiency (N) significantly decreased the CO_2 assimilation rate in pak choi and romaine lettuce. Moreover, phosphorus (P) and potassium (K) deficiencies notably reduced the CO_2 assimilation rate in romaine lettuce. Conversely, an excess of nutrients in the 150% and 200% treatments enhanced the CO_2 assimilation rate in pak choi compared to the control treatment.

Environmental parameters, nutrient solution characteristics, and vegetation indices, which statistically impact the photosynthetic rate, serve as input parameters for constructing ANN models to predict the photosynthetic rate of leaf vegetable crops. In the development of ANN models, input parameters are the primary factors that determine the magnitude of the output parameters (Suhardiyanto 2023). In this research, an ANN model has been effectively constructed to predict the CO_2 assimilation rate of leaf vegetable crops, comprising nine parameters in the input layer, ten hidden layers, and one parameter in the output layer. As depicted in Figure 7, the gradient value approaches 1, and the intercept is close to 0 in the ANN model's training and validation results. This indicates a close correspondence between the predicted and actual measurement values of the CO_2 assimilation rate. In addition, the higher R^2 value or close to 1 and the lower RMSE value indicate the performance of the ANN model with excellent accuracy (Suharto 2016). Hence, the ANN model demonstrates proficient prediction capabilities for the CO_2 assimilation rate in hydroponically cultivated leaf vegetable crops within the greenhouse. Through ANN modeling, the system can effectively learn and discern patterns within CO_2 assimilation rate data, elucidating the intricate relationship between input parameters and the CO_2 assimilation rate of leaf vegetable crops (Lenni *et al.* 2020). Statistical analysis and ANN modeling complemented and strengthened each other in explaining the relationship and influence of input parameters, especially nutrient stress conditions, on the photosynthetic rate of leaf vegetable crops cultivated hydroponically in a greenhouse.

An optimal photosynthetic rate will affect the increased productivity of leaf vegetable crops. Therefore, farmers can increase the productivity of leaf vegetable crops by paying attention to the availability of nutrients for plants in optimal conditions. In addition, developing the photosynthetic rate model can provide an overview for farmers to understand what factors affect the photosynthetic rate, which has implications for increasing leaf vegetable crop productivity. So that farmers can predict how changes in the input parameters of the ANN model will affect the productivity of leaf vegetable crops cultivated hydroponically in the greenhouse.

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